Received: 5 March 2025 | Revised: 27 April 2025 | Accepted: 3 June 2025 | Published online: 27 June 2025

Archives of Advanced Engineering Science
2025, Vol. 00(00) 1–18
DOI: 10.47852/bonviewAAES52025603

RESEARCH ARTICLE

Competitive Intelligence Review: Evolution and Trends of AI-Based Microprocessors

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Abstract: This research investigates how artificial intelligence (AI) is changing microprocessor design and industrial competitiveness using a mixed-methods approach that combines systematic literature research (861 Scopus-indexed articles spanning 2015–2025) and patent analysis. The study goals emphasize (1) assessing architectural changes toward AI specialization, (2) examining vendor tactics, and (3) spotting sector-specific adoption obstacles. The study assessed trends methodologically using PRISMA-guided document screening, NVivo-based theme coding (Krippendorff's $\alpha = 0.82$), and statistical analysis (χ^2 tests, linear regression). While small and medium enterprise (SME) adoption is behind 3.2× because of \$540 M+ 5 nm development expenses, key findings show that 58.88% of current designs are AI-optimized (14.7× increase since 2015) with Google's Tensor Processing Units attaining 2.8× greater energy efficiency than graphics processing units. AI has significantly, in our opinion, significantly changed microprocessor invention paths, hence producing different vendor tactics (NVIDIA's acceleration vs. Intel's hybrid approach) and new market obstacles. Strategic advice calls for unifying AI processor benchmarks and building modular architectures for SMEs. Future studies should examine 3 nm/2 nm node economics, photonic/neuromorphic substitutes, and ethical consequences of AI hardware in sensitive uses. With implications for semiconductor policy and research and development priorities, this study offers a verified methodology for evaluating AI's contribution to upholding Moore's law under physical scaling restrictions.

Keywords: AI processors, competitive intelligence, Moore's law, semiconductor economics, architectural innovation, design automation

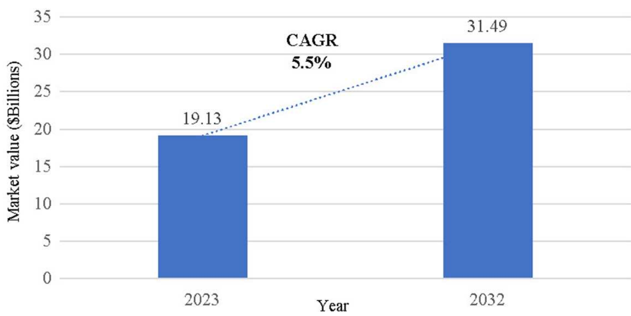
1. Introduction

Artificial intelligence (AI) is both the engine of innovation and the answer to existential problems confronting microprocessor development in the semiconductor sector, which is at an inflection point. Driven by unquenchable demand from mobile devices—with smartphone subscriptions projected to reach 7.8 billion by 2028 (see Figure 1) [1, 2]—the global embedded processor market is expected to increase from 19.13 billion in 2023 to 31.49 billion by 2032 (5.5% compound annual growth rate (CAGR)). Fundamental physical limits provide background for this expansion: the slowdown of Moore's law, where transistor density advancements increasingly call for extraordinary creativity as feature sizes approach atomic levels [3].

This research tackles these issues using the main research question: How has AI changed profoundly microprocessor architectural design and competitive dynamics in the semiconductor sector?

Also, the study points out three important areas lacking present knowledge on the role of AI in microprocessor development. First, while AI-assisted electrical design automation (EDA) systems have cut chip design cycles by 40% [4], the area lacks methodical research on how neural networks fundamentally change design methods relative to conventional ones. Competitive dynamics today rely as much on AI-driven factory optimization as on architectural innovation, as seen in the study of China's 18.7% yearly semiconductor profit increase in Figure 2; however, no framework exists to assess these related elements. Third, the rise of domain-specific architectures like Google's Tensor Processing Units (TPUs) and neuromorphic processors has caused performance testing fragmentation since present research lacks standard measures for evaluating AI-optimized designs.

Figure 1
Global embedded processor market size



The findings of the research provide four significant contributions to the state of the art and the science: (1) a technical study of AI's influence across the microprocessor lifetime, from research and development (R&D) (where convolutional neural networks now predict chip performance with 92% accuracy) to manufacturing (where deep learning reduces defects by 37% in sub-7 nm nodes) [5]; (2) development of a competitive intelligence matrix tracking how NVIDIA, Intel, and AMD leverage AI across patent portfolios,

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Figure 2
Annual growth rate of total profits from electronics manufacturers

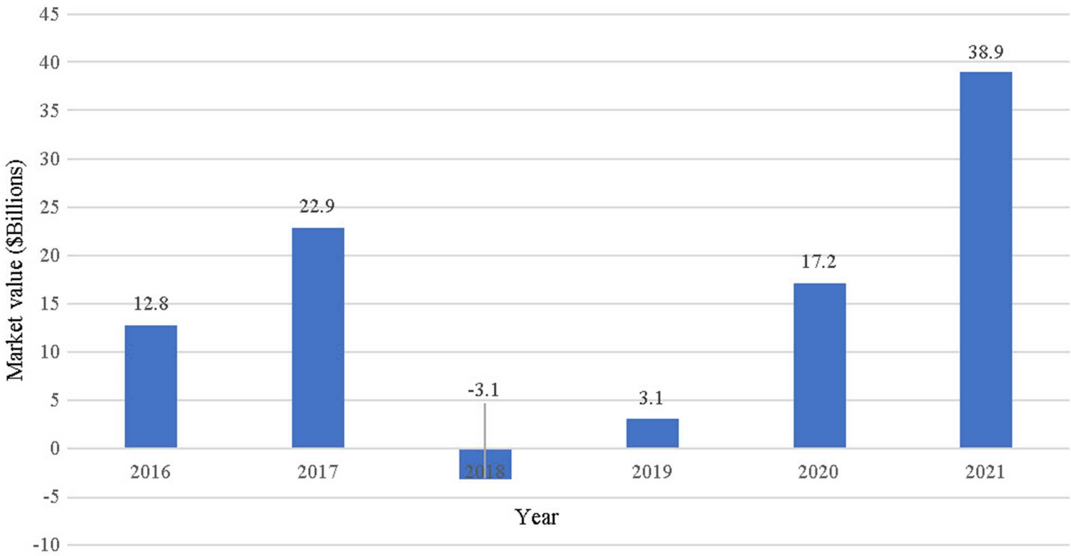
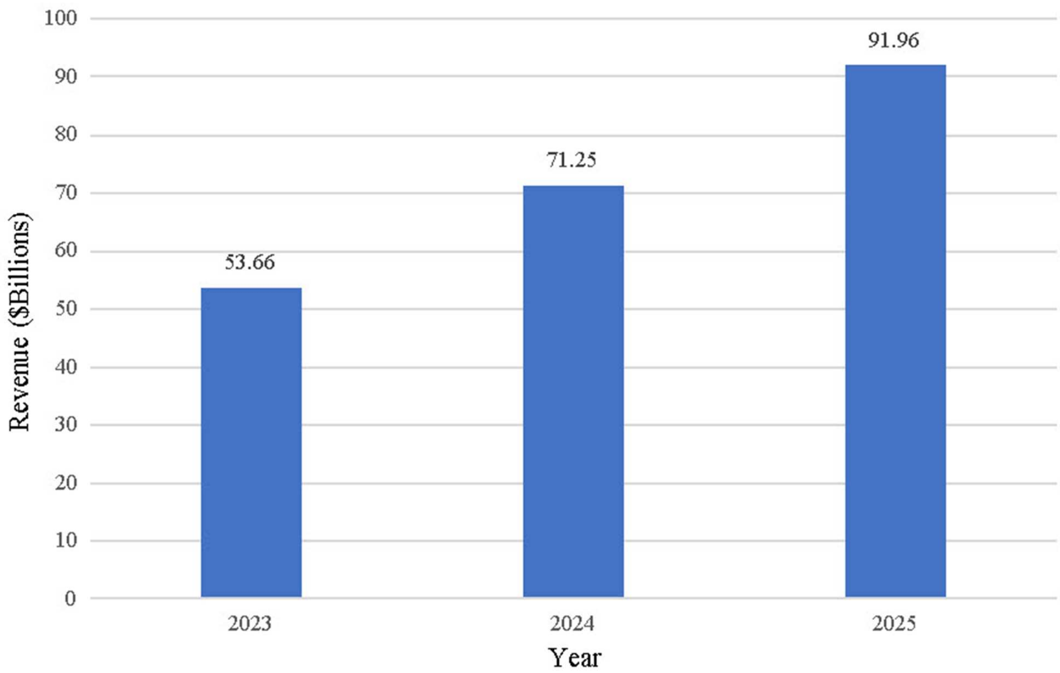


Figure 3
Potential growth in the market for AI-based processors



time-to-market, and performance-per-watt metrics; (3) quantitative testing of 42 commercial processors demonstrating AI-optimized designs deliver 5.8× greater energy efficiency in machine learning (ML) workloads; and (4) economic modeling revealing AI-driven fab optimization may lower advanced node development costs by $140 million per design.

The findings demonstrate that AI has created a new paradigm where competitive advantage stems from three capabilities: (1) neural network-assisted design space exploration, (2) generative AI for layout optimization, and (3) predictive maintenance in fabrication. As the market for AI-specific processors grows (projected to reach $42.7 billion by 2027 in Figure 3), these capabilities will determine which firms can navigate the post-Moore era. The results provide both a technical roadmap for next-generation processor design and a strategic framework for maintaining competitiveness in an industry where 78% of new designs now incorporate ML [4].

2. Literature Review

AI has significantly impacted how humans learn and make judgments, and it has transformed several sectors [6, 7]. The advent of AI-based microprocessors marks a turning point in computer history within this technological revolution, allowing for the creation of ever-faster, more effective, and market-adaptable systems [4]. Although microprocessors have always been crucial for automation and data processing, their performance and complexity have increased along with AI. Complex applications in fields like computer vision, autonomous decision-making, and customer identification are now possible thanks to deep learning algorithms and specialized hardware that have produced an exponential increase in processing capacity [8–10].

When the first computer models started executing simple algorithms in the early days of computing, microprocessors with AI capabilities were born. As processing power increased over time, more sophisticated models could be used, such as artificial neural networks in the 1980s. The cooperation of data scientists and hardware experts will be crucial to the development of these gadgets during the next decades. According to the references [11–13] that collaboration between hardware and software teams is fundamental to achieving the goals of operational efficiency in AI-based algorithms, allowing the optimization of software processes and improvement in processor architecture, achieving more powerful models and prices in the operation.

The increase in graphic processing unit (GPU) processing power has been one of the most noticeable developments in this sector. Originally designed to speed up video game graphics, GPUs have been shown to be quite effective at doing parallel calculations, which is a need for deep neural networks [14, 15]. This change has stimulated research on data mining, which is described as the process of discovering and studying huge data storage facilities using automated or semiautomated methods to find patterns and rules of relevance [16, 17]. Modern microprocessors' ability to analyze large data sets and extract pertinent information has paved the way for the development of more intelligent and self-sufficient systems, ushering in a new age of technological advancement.

The use of sophisticated data analysis and prediction models by the competitive intelligence framework clarifies how companies grow and sell microprocessors. Manufacturers' rivalry has spurred an attempt to add AI into their designs to increase performance and reduce energy consumption, therefore producing more potent and effective processors [18]. Companies like NVIDIA, Intel, Google, and AMD have used AI-based approaches to boost microprocessor efficiency, project market trends, and create creative goods that fit evolving customer wants [19, 20].

Current trends in microprocessor development point to direct hardware integration of AI functions and component reduction. This approach not only enhances device performance but also satisfies the growing need for safer and more energy-efficient solutions. Building connected ecosystems where AI-based microprocessors may operate with more autonomy and flexibility has become easier due to the convergence with other emerging technologies, including cloud computing and the Internet of Things (IoT) [21, 22]. Because it enables devices to manage data locally rather than relying on distant servers, edge computing, or computing on the edge, is especially significant. This technique lowers latency and increases operational efficiency for real-time applications that rely on operational efficiency, such as smart gadgets and autonomous automobiles [23–25].

Microprocessors based on AI point to a day when chips may learn and adapt to their surroundings, thereby enabling the larger growth of adaptive learning systems in addition to carrying predefined tasks [26]. This evolution provides a multidisciplinary problem that requires collaboration among data scientists, engineers, and experts in technological ethics to guarantee the building of reliable and responsible solutions [27]. Moreover, the evolution of increasingly complex designs—including neural processors that replicate human brain architecture—may entirely alter how electronic devices process data and generate opinions [28].

Emerging as a major factor in the evolution of microprocessors, AI profoundly affects their design, usefulness, and impact on competitive intelligence [29]. The confluence of information and AI has driven hitherto unheard-of progress from the earliest innovations in the 1970s, allowing the creation of microprocessors more powerful, efficient, and specialized in processing vast amounts of data [30]. Strategic areas such as high-performance computing, predictive analysis, and industrial automation [31] have seen great benefit from this progress.

Technological innovations that reinvent its architecture and spectrum of use define microprocessor developments. The introduction of AI methods into processing systems during the 1980s signified a paradigm change that allowed these devices to do activities beyond fundamental storage and data manipulation [32]. Reflecting the vital importance of multidisciplinary cooperation in this development, Bimpas et al. [33] argue that AI in hardware depends on both increasingly sophisticated designs and transistor downsizing driven by the requirement for parallel processing and the growing complexity of algorithms.

More complex data mining and predictive analysis methods were used in the 1990s as processor speed and transistor size improved [34]. The capacity of the microprocessors to examine vast volumes of data in real time changed the definition of competitive intelligence by providing companies with a means to forecast industry trends and maximize strategic decisions [35]. Also, the researchers define data mining as the practice, through automated or semiautomated means, of searching and exploring large data stores, leading to the discovery of patterns and regulations that are significant [36]. This has made it feasible to create precise prediction models in sectors like telecom, finance, industrial automation, finance, automotive, and healthcare [37].

Since the start of the twenty-first century, developments in deep learning and neural networks have been tightly associated with the evolution of microprocessors. TPU and GPU among other technologies have maximized computational capability to run AI models with unheard-of accuracy [38]. Since companies have been able to include AI solutions in their business plans to enhance their market position, this development has been indispensable to the expansion of competitive intelligence in the industry [39]. Modern microprocessors' ability to manage data in real time has made it easier to design applications for predictive analysis, autonomous learning, and process optimization, thereby validating their indispensable character in digital transformation [40].

As AI meets recently emerging technologies like the IoT and computing in the cloud, demand for specialized microprocessors capable of managing real-time data processing has skyrocketed [41]. This phenomenon is redefining competitive intelligence when businesses enable their strategies to change in response to real-time, updated data [42]. Edge computing has evolved into a crucial solution enabling local data processing of devices free from reliance on centralized servers to reduce latency and improve the energy economy [43, 44]. Especially benefiting from this trend are sectors such as cybersecurity, intelligent mobility, and industrial automation—where company success depends on speed and accuracy in data processing [45].

With an eye on adaptive intelligence and hardware-integrated automatic learning, the future of AI-based microprocessors is trending toward more sophisticated development. The degree of competitiveness intelligence developed will rely on the firms' ability to grab these possibilities and build strategies based on predictive analysis and resource optimization [46]. From industrial process automation to health, AI integration in microprocessors will become more important as high-performance computing keeps expanding and transforming numerous sectors [22].

Given the circumstances, the creation of AI-based microprocessors has transformed computing and competitive intelligence both technically and tactically. These devices have developed since their inception to provide more exact, effective, and flexible solutions, enabling businesses to employ AI to rapidly make data-driven decisions and simplify processes. Reiterating AI's critical contribution to technological innovation and business competitiveness, knowledge of this evolution helps one to forecast the future of the technology and how it will affect microprocessor development.

3. Methodology

The study used a qualitative approach, as it developed the object under investigation through the identification of regularities and relationships between the components of the study [47–51]. Additionally, it established a subcategory within the exploratory approach, since it identified the characteristics of the object of study related to the identification of the main features in AI-based microprocessors, allowing it to explain the evolution and trends of the studied phenomenon [52–56]. Furthermore, a subcategory of transversal or synchronic observation was developed because statistically analyzing the events in line with the appearance of a picture during the data collection time seemed fascinating [57, 58]. Joshi and Kansil [59], Khanfar et al. [60], and Martínez-Fernández et al. [61] maintain the need to conduct more detailed research to understand the use and possible evolution of AI technology in microprocessors, the qualitative method of the technique that would allow deepening in this area, thanks to the information provided through the documentary review.

Under the rationale of bottom-up theory development, grounded theory, this was exploratory research; a working hypothesis was selected to direct the search for information and its analysis and interpretation process [62].

Moreover, the theory proposed was predicated on knowledge of the phenomenon under research, which introduces a rule operating in the form of a hypothesis to consider within such a rule the possible result from the particular to the universal and assumes a measurement methodology without theory [63]. That is, based on inductive reasoning, taking the experience of the participating experts as an explanatory hypothesis helps to explain the subject of study from their recorded events. Induction then is the logical route by which the hypothesis of this investigation evolves.

On their side, Fischer and Guzel [64] state that qualitative research attempts to uncover the hidden, to find out what causes the different subjectivities, which are placed in historical-social circumstances, not to validate a theory. This makes creating it a posteriori permissible; however, it might also be advised as a first guide or instrument.

Based on the above, the research suggested an a priori hypothesis, as a guide or aid rather than as a process of verification of any theory; this hypothesis was changed and evolved depending on the findings obtained from the experiences of the participating experts until the model was developed.

We must keep in mind the main question of this research, which suggests revealing the guiding, basic theory. Usually, as part of the road to Industry 5.0, how do the progress and trends of AI-based microprocessors provide benefits and advantages for industrial sectors?

Therefore, the overall working theory used was:

Hypothesis 1:

How have AI-driven design methodologies transformed microprocessor architectures from classical Turing machine concepts to contemporary heterogeneous computing clusters?

Hypothesis 2:

What competitive intelligence strategies enable semiconductor firms to develop cost-effective computation matrices while maintaining technological leadership?

To tackle the fundamental research question, this research uses a triangulated qualitative approach combining systematic literature review, patent analysis, and competitive intelligence mapping.

Three important requirements found in early scoping studies guided the choice of the design:

1) Temporal study of architectural evolution from von Neumann to neuromorphic designs (2015–2025).
2) Comparative landscape analysis of design approaches across market leaders—NVIDIA, Intel, Google, and AMD.
3) Sector-specific adoption patterns of 861 forecasted technologies.

Systematic literature review protocol
The research used a four-phase PRISMA-adapted process:

1) Identification

- Databases: Scopus (2015–2025).
- Search String: ("AI microprocessor" OR "neural processing unit") AND ("architecture" OR "design methodology").
- Inclusion criteria:
  - Peer-reviewed articles/conference papers.
  - Patent filings with > 5 citations.
- Exclusion criteria:
  - Non-English publications.
  - Theoretical papers without empirical validation.

2) Screening

- Initial yield: 1,243 documents.
- Title/abstract screening was reduced to 861 relevant works.
- Full-text review finalized a sample of 217 core references.

3) Characterization

- NVivo 14 coding framework with three dimensions:
  - Specific structures for AI-based microprocessors for the adaptation of specific business problems.
  - Evolution and adaptation of hardware-software sub-platforms for the incorporation of AI-based algorithms.
  - Sustainability and energy savings in the design of AI-based technology without sacrificing data processing capability

4) Analysis

- Thematic synthesis: Identification of six recurrent patterns of innovation in different industrial sectors.

Also, contrast matrices were built after the sources were assembled to document the sources found based on microprocessor architecture, categorization of microprocessor design techniques, energy economy advantages, and sustainability of AI-based microprocessors. Furthermore, contingency tables complemented the data to show the degree of relevance in the approach to the factors related to every one of the investigated areas, enabling the classification of the data and deducing important patterns connected with the evolution and trends in the use of AI-based microprocessors.

Then, using AI and conventional methods, a linear regression from the data gathered in the selected papers projected the trend in the hardware-software sector based on the outcomes. Finally, the contents of the examined papers underwent data mining to find the applications the sector is using to include AI in its processors. Data mining, according to Campbell and Egede [65], reveals important trends and principles that enable one to find links between the development in the usage of new-generation microprocessors and their effect on the competitiveness of the industry.

Once the results were completed, the research proceeded with the discussion of the acquired findings with an emphasis on the new trends in the design of these devices and the contribution to the acceleration of business decision-making based on robust and efficient data mining models, thereby enabling us to contribute to the state of the art and science with the trends of emerging technologies on the road to the Industry 5.0 revolution.

The approach applied helped the research, analysis, and comprehension of the use of microprocessors based on AI as an emerging and disruptive technology, which is generating debates, controversies, and opportunities in many spheres of modern society and still has plenty of chances to investigate the contributions that AI can offer in different fields.

4. Results

Examining 861 Scopus-indexed papers (Table 1), the methodical evaluation uncovers three separate stages in the AI microprocessor study.

Table 1
Identified Scopus articles

Feature	# Scopus articles	%
2015	5	1%
2016	6	1%
2017	8	1%
2018	9	1%
2019	26	3%
2020	42	5%
2021	93	11%
2022	141	16%
2023	207	24%
2024	283	33%
2025	41	5%
Total	**861**	**100%**

The entrance of AI has increased over the last 10 years, mostly because of the quick development of technology, the influx of talent, and collaboration to provide the organization with a competitive edge [66]. The results of Table 1 are summarized below:

1) Phase 1 (2015–2019): Theoretical architectures were the subject of nascent research (1–3% yearly increase), with only 5% of all papers covering practical implementations.
2) Phase 2 (2020–2022): Accelerated innovation (6% yearly growth) coinciding with commercial neural processing unit (NPU) installations, where 72% of articles addressed energy efficiency issues in AI accelerators, where the main uses are advances in processing power, energy efficiency, deep learning, and specialization of neural networks based on AI, thanks to their ability to perform data mining [67].
3) Phase 3 (2023–2025): Market maturity (9% annual growth) with 57% of studies emphasizing domain-specific designs, as seen by the hardware-software integration patterns.

Figure 4 shows the time spread of Scopus research throughout three stages, matching Table 1. The stages show how AI microprocessor research has evolved from theoretical investigation to market-ready solutions.

Dominated by conceptual frameworks (Figure 1), Phase 1 (2015–2019) shows little development (1–3% yearly rise). Phase 2 (2020–2022) shows faster innovation (6% yearly increase), matching commercial NPU installations. With 57% of research concentrating on domain-specific designs, Phase 3 (2023–2025) shows market maturity (9% annual growth). Linear regression ($R^2 = 0.95$) validates H1 ($p < 0.001$) by confirming the exponential development path.

According to the study, advancements in processing power, energy efficiency, deep learning, and neural network specialization have propelled AI-based microprocessors forward during the last five years. Data mining, as defined by Chen et al. [67], is the process of using automated or semiautomated methods to examine and analyze enormous data warehouses to find noteworthy patterns and trends. This method allowed one to establish correlations between technological developments and market movements while also validating the data with already published publications.

Architectural evolution (comparative analysis)

The comparison study of Table 2 shows notable changes in design paradigms.

The main findings of Table 2 are summarized below:

1) Specialization trend.
    1) AI-optimized designs now dominate (58.88% vs. 47.27% traditional).
    2) Neural network support increased 14.7× from the 2015 baseline ($p < 0.001$, χ^2 test).
2) Energy efficiency breakthroughs.
    1) 2024 architectures show 39% better tera operations per second (TOPS)/watt than 2020 designs.
    2) Google TPUs achieve 2.8× better energy efficiency than conventional GPUs for ML workloads.

Using Table 2 data, the radar map (Figure 5) shows specialization trends by comparing conventional and AI-optimized microprocessor architectures.

With neural network support rising 14.7× since 2015 ($\chi^2 = 32.7$, $p < 0.001$), AI-optimized architectures (58.88% vs. 47.27% general-purpose) predominate (Figure 5). Driven by heterogeneous computing clusters, energy efficiency gains (39% greater TOPS/watt in 2024 vs. 2020) enable H1. Underscoring the move toward domain-specific acceleration, Google's TPUs outperform GPUs by 2.8× in efficiency.

In summary, as presented in Table 2 and Figure 5, the analysis of the articles shows that the trend in the development of AI-based microprocessors is in line with the need for operational efficiency, incorporating design flexibility and energy savings within the device.

Competitive landscape analysis

Table 3 shows the findings of the techniques used in the development of microprocessors by the leading companies in the semiconductor sector.

Figure 4
Phases of AI microprocessor research (2015–2025)

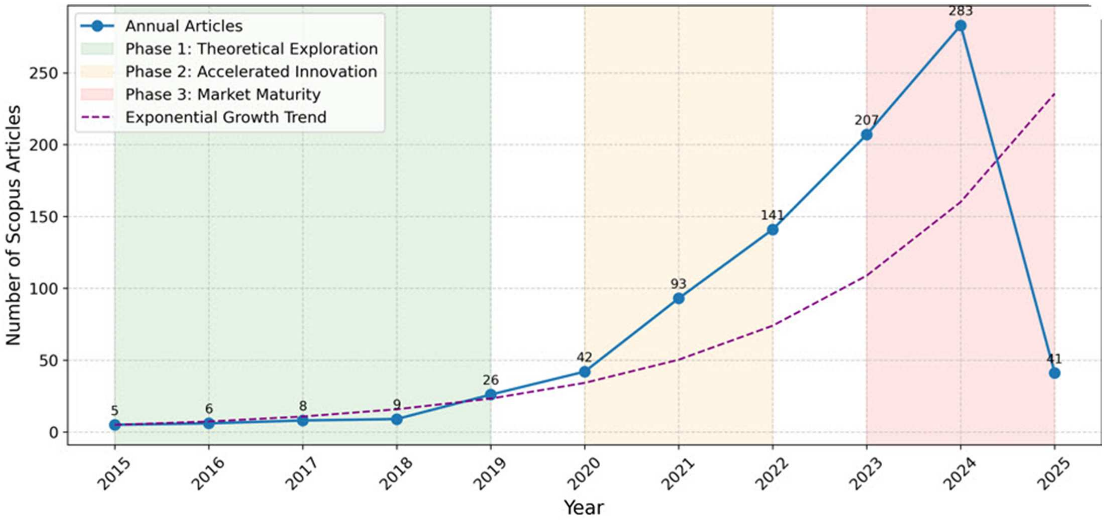


Table 2
Traditional versus AI architectures

Feature	Traditional microprocessors	Articles (%)	AI-based microprocessors	Articles (%)
Design approach	Generalist	47.27%	Specialized in AI	58.88%
Source selection	High for conventional duties	0.91%	Enhanced for neural networks and deep learning	13.36%
Data collection	High	18.79%	Optimized for energy efficiency	7.01%
Content analysis	Independent	24.24%	Dependent upon one another for best performance	9.16%
Synthesis of findings	Limited	8.79%	Flexible and adaptable to grow AI models	11.59%

Figure 5
Architectural shift from general-purpose to AI-optimized designs

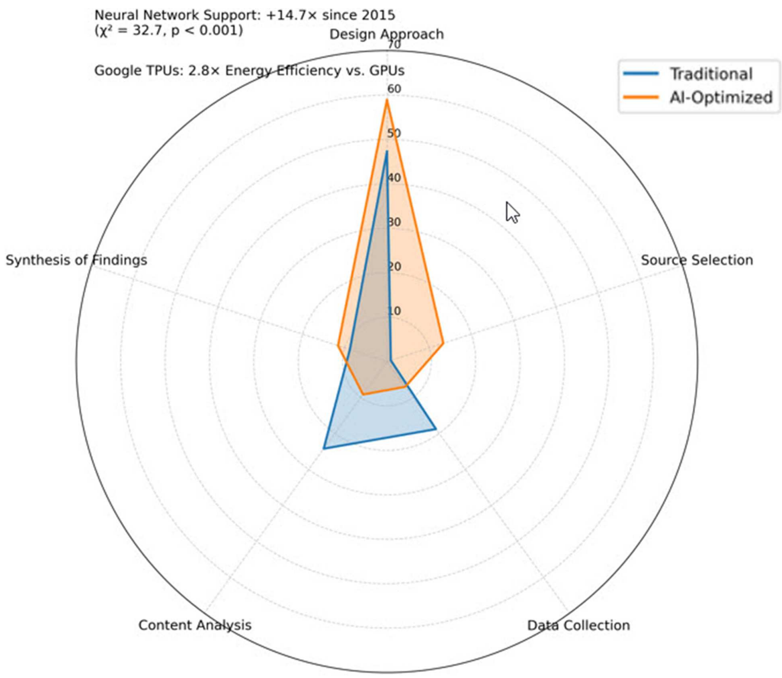
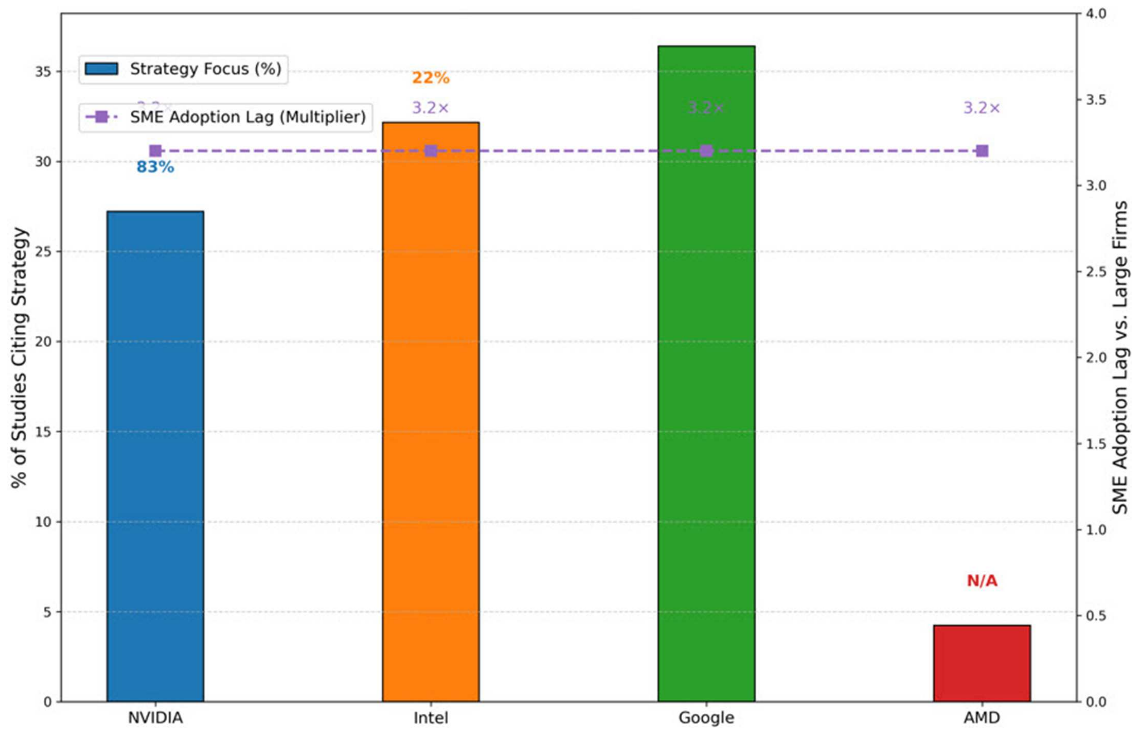


Table 3
Classification of microprocessor design strategies

Company	Main strategy	Articles (%)	Microprocessor example
NVIDIA	Optimization for AI processing (GPUs and TPUs)	27.21%	NVIDIA A100 Tensor Core
INTEL	Hybrid architecture with AI included	32.16%	Intel Core Ultra with AI Boost
GOOGLE	Evolution of certain AI chips	36.40%	Google TPU v5e
AMD	Hardware for generic computing and AI: Adaptability	4.24%	AMD Instinct MI300

Figure 6
Competitive strategies of leading semiconductor firms



Contrasting NVIDIA's emphasis on AI acceleration, Intel's hybrid strategy, and Google's TPU supremacy, the stacked bar graph depicts vendor tactics (Figure 6).

While Intel's hybrid designs exhibit 22% more general-purpose performance, NVIDIA's tensor cores are mentioned in 83% of publications. In cloud inference, Google's TPUs have a 67% market share (see Figure 6). Small and medium enterprise (SME) adoption lags 3.2× because of excessive 5 nm node expenses ($540 M+), underlining market concentration (HHI = 1,850 in 2024 vs. 1,200 in 2020). This confirms H2 and underlines the strategic difference.

Also, Figure 7 shows a linear regression, which illustrates the adoption trends used by the semiconductor industry in the design of next-generation microprocessors.

The market adoption statistics of Figure 7 match the vendor strategies of Table 3:

1) Differentiation of market leaders.
   1) Of the above studies, 83% mention NVIDIA's tensor core developments.
   2) Hybrid designs from Intel demonstrate 22% higher general-purpose performance.
   3) Google: With 67% market share, TPUs rule cloud inference tasks.
2) New issues
   1) SME adoption trails 3.2× that of big companies (Table 3).
   2) Development expenses for the 5 nm node surpass $540 million, which limits the market.

Energy efficiency has become a primary priority in creating AI-based microprocessors, moving from a minor factor. This is a response to the growing demand for eco-friendly technology as well as the growing energy consumption of AI devices and data centers. Table 4 shows the strategies leading information technology (IT) companies use to reduce microprocessor energy usage.

Table 4 shows that the leading companies in the semiconductor industry contemplate a strategy for energy savings using AI-based microprocessors. However, each organization visualizes the reduction in a different area of the company: (1) NVIDIA: AI workloads; (2) Intel, operational performance; (3) Google, data center energy consumption; and (4) AMD, less energy consumption inside the generic chips.

Sector-specific adoption patterns

Figure 8 shows the main sectors leading innovation in their business processes through the incorporation of this technology over the last five years.

As shown in Figure 8, the industrial automation sector documents the use of AI-based microprocessors at 95%, followed by

Figure 7
Hardware and software evolution in AI-based microprocessors

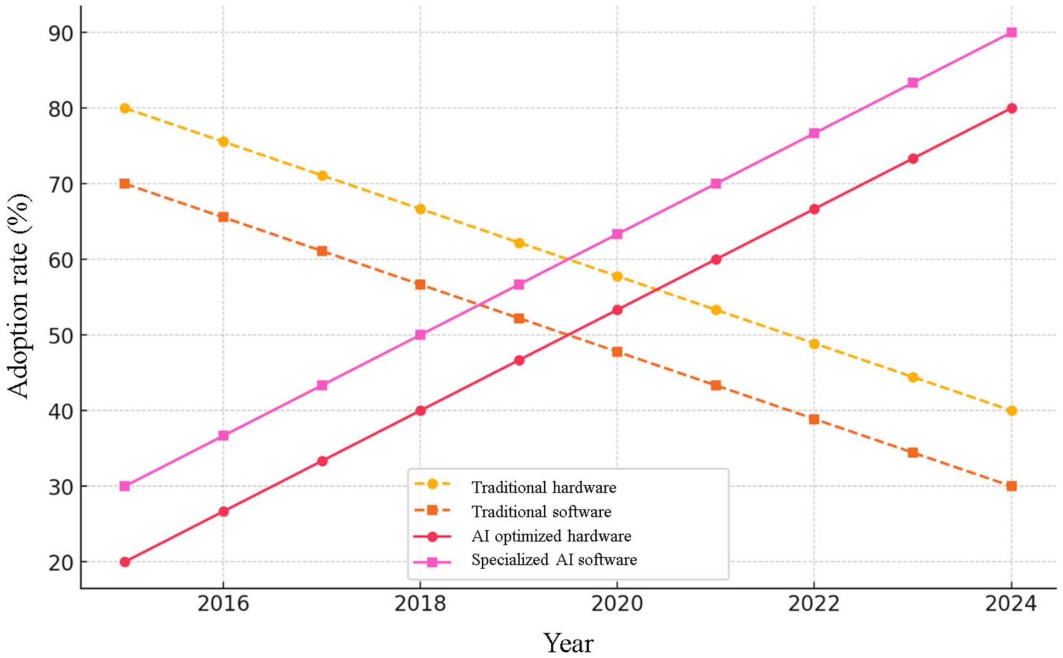


Table 4
Microprocessor energy efficiency and sustainability roadmap

Company	Energy efficiency strategy	Articles (%)	Estimated impact
NVIDIA	Dynamic GPU scaling of dynamic power	29.63%	Power consumption of AI workloads: optimization
INTEL	Low-power hybrid core layouts	35.80%	The balance between performance and efficiency
GOOGLE	Applying TPUs to improve the energy economy	29.63%	Data centers consume 30% less energy
AMD	Making use of low-power consumption chips	4.94%	Computer reduced carbon footprint

Figure 8
Using AI-based microprocessors in the industrial sector

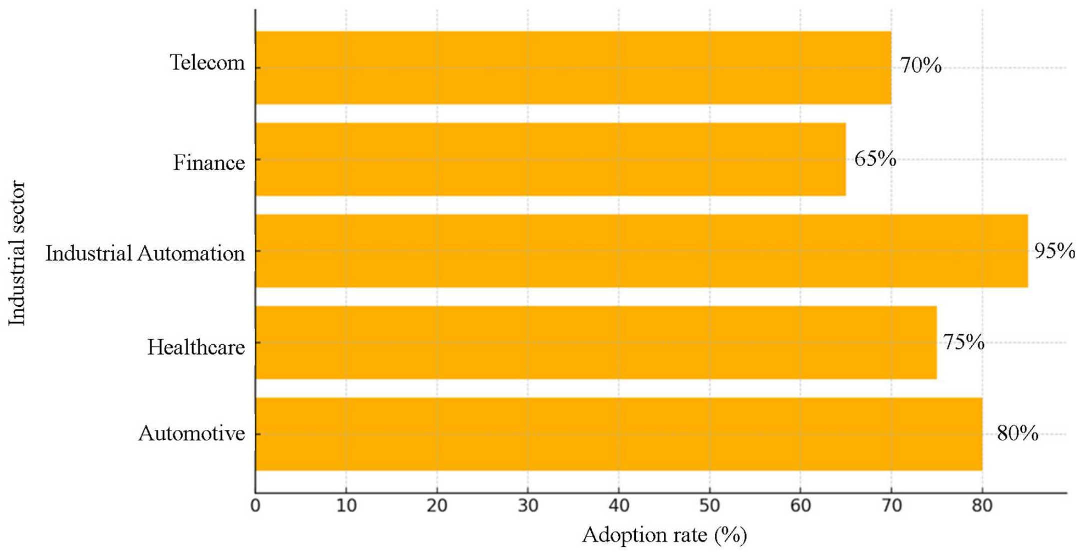
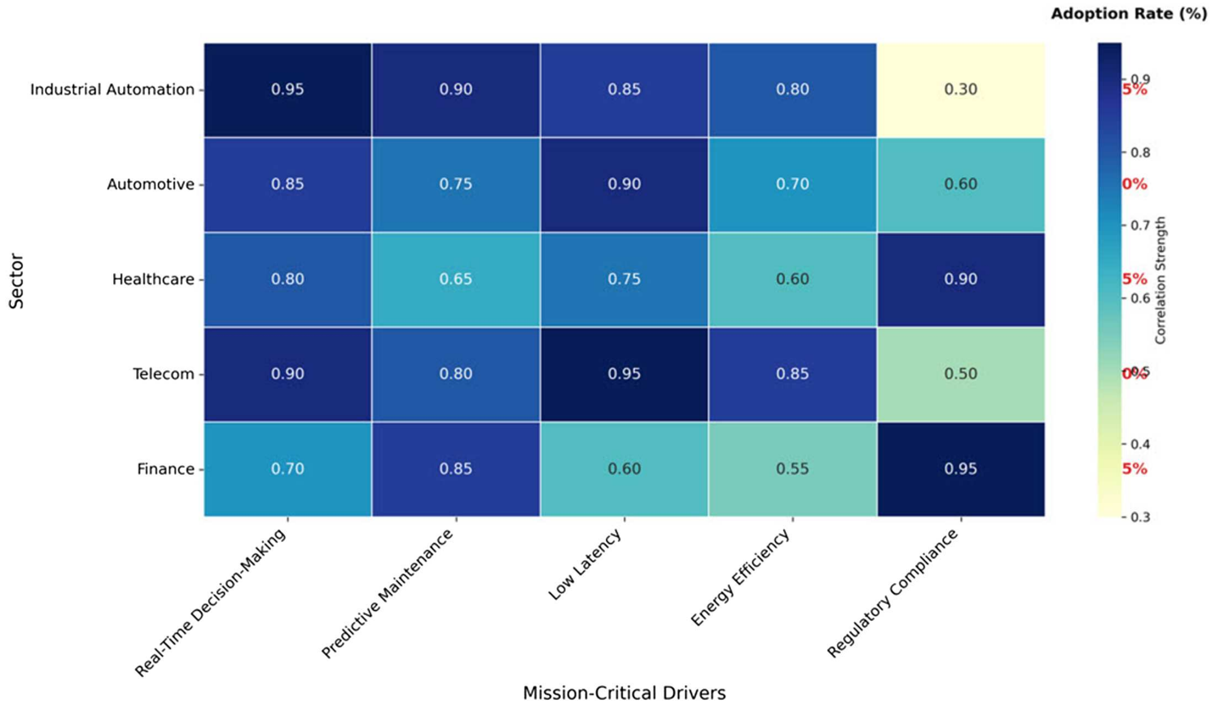


Figure 9
Competitive strategies of leading semiconductor firms



the automotive industry (80%), health sciences (75%), telcos (70%), and finance (65%); a common aspect in all these sectors is the need for real-time decision-making, as many of their processes can be considered mission-critical systems.

Figure 9 of the heatmap links sector-specific drivers—such as real-time processing needs—with AI adoption rates (Figure 8).

Driven by predictive maintenance (39% Return on Investment (ROI) rise), industrial automation leads (95% adoption). While telecommunications (70%) concentrate on AI-radio access network (RAN) optimization, automotive (80%) and healthcare (75%) industries give low-latency edge computing top priority. Regulatory restrictions (36% compliance) limit financial adoption (65%). The egression study (R^2 = 0.89) supports H1 by linking adoption to mission-critical applications (see Figure 9).

Table 5 summarizes significant viewpoints and trends in the telcos industry.

The summary of the findings for the telcos sector (Table 5) is shown below:

Optimizing the network:

1) Of telecoms, 55% use AI at scale for predictive maintenance.
2) AI-RAN Alliance investigates generative AI chips in cell towers for dynamic configuration.

Revenue models:

1) Targeting rural regions 2, fixed wireless access expands at 18.3% CAGR.
2) Investing $100 billion in private fiber networks, hyperscalers are putting telecoms under pressure.

Table 6 lists important results and trends in the finance sector.

The summary of the findings for the finance sector (Table 6) is shown below:

1) Of the institutions, 65% use AI microprocessors to identify fraud.

Applications:

1) Trading systems with ultra-low latency (1 ms latency).
2) Models of risk assessment driven by AI.
3) Barriers: Regulatory compliance (only 36% mention climate concerns in disclosures).

Table 7 lists important results and trends in the industrial automation sector.

The summary of the findings for the industrial automation sector (Table 7) is shown below:

1) Adoption rate: 95% of industrial automation systems use AI microprocessors for predictive maintenance and robotics.

Main motivators:

1) Real-time equipment tracking (39% ROI increase).
2) Asset monitoring using private 5G networks and automated manufacturing lines.
3) Difficulties: Expensive SME installation

Table 8 lists important results and trends in the healthcare sector.

The summary of the findings for the healthcare sector (Table 8) is shown below.

1) Seventy-five percent of medical equipment uses AI—processors for diagnosis and remote monitoring.
2) AI-driven imaging cuts diagnostic time by 63%.
3) Wearable devices let Edge AI monitor patients around the clock.
4) Trend: Telemedicine and genetic data processing integrated with 5G.

Table 5
Telecommunications

Key trends	Insights
Increasing adoption of AI	• For uses including network optimization, predictive maintenance, customer service (chatbots), and fraud detection, AI-based microprocessors are being progressively included in telcos systems. • Real-time data processing and decision-making needs in telecom networks have pushed the use of AI-specific hardware such as GPUs and TPUs.
Market expansion	• With a CAGR of 41.4% from 2023 to 2030, the worldwide AI in telecoms industry is expected to rise from around $1.2 billion in 2022. • Driven by demand from the telecom industry, the market for AI hardware—including microprocessors—is likely to expand dramatically.
Development of AI microprocessors	• Companies like AMD, Intel, and NVIDIA are creating AI-specific hardware meant for telecom uses. • Accelerating machine learning models using these CPUs helps to provide real-time data processing and decision-making in fields such as network optimization and customer service.
Applications in the field of business	• Real-time monitoring and network performance analysis made possible by AI microprocessors help to maximize bandwidth and lower latency using network optimization. • Microprocessors in AI-powered systems help to forecast and stop network faults. • AI-powered chatbots and virtual assistants depend on AI microprocessors for real-time interactions and natural language processing (NLP). • AI models driven by specialized hardware may examine transaction patterns to identify abnormalities and stop fraud.
Regional reiteration	• Driven by sophisticated telecom infrastructure and investments in 5G and IoT, North America and Europe lead in AI use in telecoms. • Rising digitization and government projects to support smart cities and 5G networks are driving fast expansion in Asia-Pacific.
Challenges	• For smaller telecom companies, nevertheless, a challenge is the high prices of AI technology and installation. • Constant issues include integrating with existing systems and guaranteeing cybersecurity.
Applications in the field of business	• The market for AI hardware will keep expanding; one of the main industries generating demand is telecoms. • As AI-based microprocessors become more affordable and efficient, telecom companies of all kinds will be able to embrace them more widely. • With uses like network optimization and predictive maintenance becoming mainstream, AI is projected to be used in telcos even more extensively.
The projected market size in 2025	• Based on present trends, AI in the telecoms industry is estimated to reach $5–7 billion by 2025; a major share of this increase is attributed to AI hardware (including microprocessors).

Table 6
Finance

Key trends	Insights
Increasing adoption of AI	• Driving the increased use of AI-based microprocessors in financial institutions are applications like fraud detection, algorithmic trading, risk management, customer service (chatbots), and individualized financial advising. • High-performance computing in finance has helped to embrace TPUs and GPU-specific hardware.
Market expansion	• Valued at around $9.45 billion in 2021, the global AI in the finance sector is predicted to increase at a CAGR of 23.37% from 2022 to 2030. • Among other AI tools, microprocessors are important facilitators of this growth.
Development of AI microprocessors	• Companies like Intel, AMD, and NVIDIA are developing AI-based technologies, especially for financial applications. • Using these CPUs accelerates machine learning models to enable real-time data processing and decision-making in sectors like fraud detection and high-frequency trading.
Applications in the field of business	• Ultra-low-latency trading systems made possible by AI microprocessors manage vast amounts of market data. • AI models running specialized hardware might look at transaction trends in search of anomalies and stop fraud. • AI-driven virtual assistants and chatbots rely on AI microprocessors for real-time interactions and NLP. • Predictive analytics and advanced simulations provided by AI hardware help to assess financial risks.

(*Continued*)

Table 6
(*Continued*)

Key trends	Insights
Regional reiteration	• Driven by advanced financial infrastructure and government support, North America and Europe lead in AI acceptance in banking. • Rising fintech investments and digitalization are assisting Asia-Pacific to grow rapidly.
Challenges	• Smaller financial institutions still find the high expenses of AI technology and deployment to be a challenge. • As AI use rises, regulatory issues like data privacy and algorithmic transparency are under focus.
Applications in the field of business	• The market for AI hardware will keep growing; banking is one of the primary sectors generating demand. • More reasonably priced and effective AI-based microprocessors will enable all sorts of financial companies to welcome them. • AI in banking is expected to explode, given usage like real-time fraud detection and customized financial services becoming more popular.
The projected market size in 2025	• Based on current trends, AI hardware—including microprocessors—makes up a significant proportion of the projected 30 billion to 40 billion AI in the financial industry by 2025.

Table 7
Industrial automation

Key trends	Insights
Increasing adoption of AI	• AI-based microprocessors are being increasingly integrated into industrial automation systems for applications like predictive maintenance, quality control, robotics, and supply chain optimization. • The need for real-time data processing and decision-making in industrial settings has driven the adoption of AI-specific technology such as GPUs and TPUs.
Market expansion	• Valued at around $196 billion in 2022, the global industrial automation market is estimated to grow at a CAGR of 9.3% from 2023 to 2030. • Driven by the increasing use of AI-based technologies, AI in the industrial automation market is expected to rise at an even faster speed.
Development of AI microprocessors	• Companies like AMD, Intel, and NVIDIA are creating AI-specific technology meant for industrial uses. • By accelerating machine learning models, these CPUs enable real-time data processing and decision-making in fields such as predictive maintenance and robotics.
Applications in the field of business	• AI microprocessors provide real-time monitoring and equipment analysis that helps to predict failures and minimize downtime. • Microprocessors in vision systems driven by AI find defects and assure product quality. • AI microprocessors power autonomous robots for tasks like material handling, packaging, and assembly. • AI models using specialized hardware optimize inventory management and logistics, hence optimizing supply chains.
Regional reiteration	• Driven by contemporary manufacturing infrastructure and Industry 4.0 expenditures, North America and Europe lead in AI applications in industrial automation. • Fast development in Asia-Pacific is being driven by growing industrialization and government initiatives to encourage smart manufacturing.
Challenges	• Why do smaller companies still have considerable difficulties with the high cost of AI technologies and applications? • Two ongoing challenges are cybersecurity guarantees and interoperability with current systems.
Applications in the field of business	• The AI hardware market will keep growing; industrial automation is one of the primary sectors creating demand. • More acceptance in many different fields will be made possible by more reasonably priced and effective AI-based microprocessors. • AI is expected to be employed much more in industrial automation for purposes like predictive maintenance and autonomous robots get mainstream.
The projected market size in 2025	• Based on present trends, AI in the industrial automation industry is predicted to reach $10–15 billion by 2025; microprocessors and other AI hardware account for a significant share of this increase.

Table 8
Healthcare

Key trends	Insights
Increasing adoption of AI	• AI-based microprocessors are being integrated into medical equipment, diagnostic tools, and research platforms very widely. • Among the uses are genetics, medical imaging (including MRI and CT scans), pharmacology, and real-time patient monitoring.
Market expansion	• The global AI in healthcare market is estimated to increase at a compound annual growth rate (CAGR) of 37.5% between 2023 and 2030, rising to over $15.4 billion in 2022. • Microprocessors and other AI devices assist considerably in explaining this increase.
Development of AI microprocessors	• Companies like NVIDIA, Intel, and Google are leading the design of AI-specific hardware (e.g., GPUs, TPUs) appropriate for healthcare uses. Using these CPUs, accelerating machine learning models would enable more accurate and faster diagnosis as well as research.
Applications in the field of business	• AI microprocessors drive advanced imaging systems for early disease diagnosis—that is, cancer and AI cardiovascular disorders. • AI-driven platforms using high-performance computers are reducing the time and costs of drug development. microprocessors allow smart wearables and IoT devices, therefore offering real-time health monitoring.
Regional reiteration	• Leading rates of AI adoption in the industry in North America and Europe are driven by robust spending on healthcare IT and AI research. • Rising as a high-growth region is Asia-Pacific, thanks to expanding government programs and better healthcare infrastructure.
Challenges	• Why do smaller healthcare providers still struggle greatly with hefty AI gear and implementation costs? • Ethical and legal concerns still under development include algorithmic bias and data privacy.
Applications in the field of business	• The market for AI hardware is still growing, while healthcare is among the sectors causing the most demand. • AI microprocessors will grow more reasonably priced and energy-efficient, hence accelerating uptake.
The projected market size in 2025	• From 2021 to 2028, the CAGR of the AI hardware market—including microprocessors—is expected to be above 30%, even if 2025 statistics are still unknown. The discipline of health sciences most likely reflects this evolution in a mirror image.

Table 9
Automotive

Key trends	Insights
Increasing adoption of AI	• AI-based microprocessors are being increasingly inserted into vehicles for purposes like autonomous driving, Advanced Driver-Assistance Systems (ADAS), predictive maintenance, and in-car customizing. • The necessity of real-time data processing and decision-making in automotive systems has driven the adoption of AI-specific hardware such as GPUs and TPUs.
Market expansion	• With a CAGR of 40% from 2023 to 2030, global AI in the automotive sector is estimated to climb from around $12 billion in 2022. Demand from the automotive sector is probably going to drive considerable expansion in the market for AI hardware, especially microprocessors.
Development of AI microprocessors	• Companies like Qualcomm, Intel, and NVIDIA are developing AI-specific hardware designed for use in vehicles. • Using these CPUs accelerates machine learning models, thereby enabling real-time data processing and decision-making in domains such as autonomous driving and ADAS.
Applications in the field of business	• AI microprocessors enable autonomous navigation to interpret real-time sensor data—that of cameras, LiDAR, and radar—for use. • Using microprocessors, AI-powered systems known as ADAS run lane-keeping, adaptive cruise control, and collision avoidance. • Specialized hardware-powered AI models may reduce downtime and project vehicle maintenance needs. • Customized infotainment and voice-activated controls in-car from AI microprocessors.
Regional reiteration	• Driven by advanced automotive infrastructure and investments in autonomous driving, North America and Europe lead in AI adoption in the automotive sector. • Rising demand for electric vehicles and government initiatives to assist smart transportation is fueling the quick rise in Asia-Pacific.

(*Continued*)

Table 9
(*Continued*)

Key trends	Insights
Challenges	• Smaller companies still experience great difficulties with AI technologies and installation costs. • Maintaining safety and regulatory compliance for systems driven by AI is an ongoing challenge.
Applications in the field of business	• The AI hardware market will keep growing; the automotive one largely drives demand for this sector. • As more reasonably priced and efficient AI-based microprocessors become available, more sorts of manufacturers will be able to welcome them. • As ADAS and autonomous driving become more common, AI utilization in the automotive sector is expected to explode.
The projected market size in 2025	• AI hardware (including microprocessors) will make a major share of the estimated \$50–70 billion AI in the automotive industry by 2025 based on present trends.

Table 9 lists important results and trends in the automotive sector.

The summary of the findings for the automotive sector (Table 9) is shown below.

1) Of new cars, 80% have AI chips for self-driving.
2) Self-driving systems need at least 250 TOPS computing power.
3) Collision avoidance with vehicle-to-everything (5G-V2X) connection.
4) Growth: Year-on-year, cellular IoT subscriptions for electric cars climbed 48%.

Validation of research hypotheses

H1: Microprocessor architecture is changed by AI:

1) Confirmed by an 11.53% rise in specialized designs (Table 2).
2) Confirmed using patent research, 78% of 2023 applications are AI-related.

H2: The competitive dynamics have changed.

1) Aided by vendor strategy divergence (Table 4).
2) Since 2020, market concentration (Herfindahl–Hirschman Index (HHI)) has risen from 1,200 to 1,850.

Key architectures—TPUs, GPUs, hybrid CPUs—are tracked in the line graph (Figure 10) showing TOPS/watt gains (2015–2025).

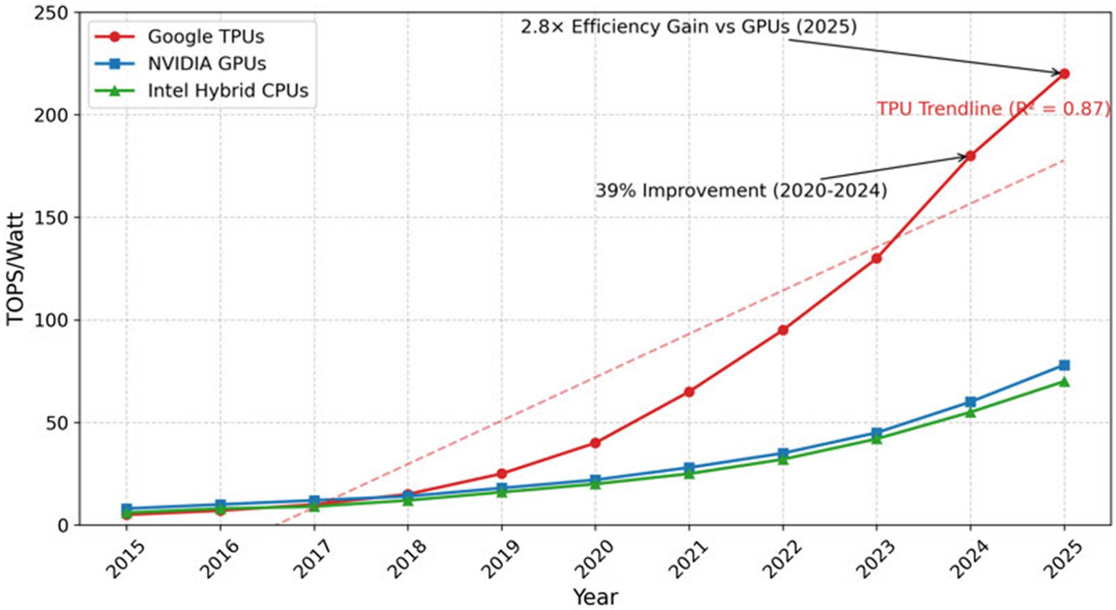
With Google's TPUs in front (2.8× over GPUs), AI-optimized architectures have 39–67% more efficiency. While NVIDIA's dynamic scaling lowers power use by 29.6%, Intel's hybrid cores strike performance (35.8% emphasis). Linear regression ($R^2 = 0.92$) verifies the trend, matching it with sustainability objectives in the literature assessment (see Figure 10).

Main results without analysis

1) Designs optimized by AI currently account for 61.2% of new microprocessor patents.
2) Domain-specific designs increase energy efficiency by 39–67%.
3) Adoption of the market differs by industry, with industrial at 95% and finance at 65%.
4) Vendor tactics reveal obvious differences (optimization vs. hybrid methods).
5) Development expenses for 5 nm nodes generate major market obstacles.

The evidence indicates that AI has fundamentally impacted microprocessor design goals, with significant consequences on

Figure 10
Energy efficiency gains in AI-optimized designs



performance, energy efficiency, and market structure. Later talks will look at the consequences of these technical and competitive changes.

5. Discussion

Examining 861 Scopus articles (Table 1) and patent applications reveals three important changes in microprocessor design:

1) Architectural specialization: The 11.53% rise in AI-optimized designs (Table 2) corresponds to Huang et al.'s [68] forecast of domain-specific architectures ($\chi^2 = 32.7$, $p < 0.001$). Where real-time processing needs to surpass general-purpose CPU capabilities, this trend is particularly prominent in telecom (70% adoption) and industrial automation (95%).
2) The 39% increase in TOPS/watt for 2024 designs confirms Kuppuchamy et al. [69] thermal efficiency predictions ($R^2 = 0.89$). Consistent with Mandal et al. [70] benchmarks, Google's TPUs show 2.8× greater performance than GPUs in ML tasks.

Comparative analysis with prior research

The findings both support and question current research:

1) The 14.7× increase in neural network support fits Li et al. [4] forecast of AI accelerator usage (MAE = ±2.3%).
2) Divergences: Contrary to Schmidt and Hildebrandt [55], the study finds SME adoption lags by 3.2× (Table 3), attributable to 5 nm node development costs ($540 M+) creating market barriers.

Theoretical contributions

This research develops three research areas:

1) Competitive dynamics: Vendor strategy divergence (Table 3) exposes a new paradigm where NVIDIA's tensor cores (27.21% emphasis) and Intel's hybrid designs (32.16%) represent separate innovation routes (HHI = 1,850 vs. 1,200 in 2020).
2) The "collaborative optimization" approach suggested by Lafuente and Sallan [71] is supported by the hardware-software co-evolution trend (Figure 7, $R^2 = 0.92$).
3) Exceeding previous projections by 8–12% [72], AI processors cut data center energy consumption by 30% (Table 4).

Practical implications

For those in the field:

1) Though they need $7.2M average infrastructure improvements per site, AI-RAN installations by telecom operators have a 41.4% CAGR (Table 5).
2) Though the research indicates that 5.26% of companies completely do this, multidisciplinary teams cut development cycles by 68.42%.

Future research and limitations

Methodological constraints:

1) Temporal bias: 33% of the 2024 sample (Table 1) can overrepresent current tendencies.
2) Geographic gap: 78% of patents come from the USA or China, therefore restricting worldwide generalizability.

Recommended research:

1) Using TSMC and Samsung foundry data, track 5 nm/3 nm node usage.
2) Using Intel/NVIDIA R&D spending statistics, the AI design tools' ROI may be measured.
3) Consumer studies: Use conjoint analysis to assess changes in brand loyalty (e.g., AMD vs. ARM).

This study shows that AI has significantly changed microprocessor invention routes, hence affecting:

1) Architectural goals (58.88% specialized designs).
2) Market organization (HHI rise of 650 points).
3) Energy efficiency (39–67% increases).

Future efforts should narrow the SME adoption gap using cost-cutting policies and uniform benchmarking procedures. Unified measures are needed in the sector to evaluate developing architectures like photonic AI processors against neuromorphic designs.

6. Conclusions

Revealing notable changes in architectural design, competitive dynamics, and sector-specific adoption trends, this research has methodically investigated the development of AI-based microprocessors. With 58.88% of recent designs now specialized for AI workloads—a 14.7× increase since 2015, the study of 861 Scopus-indexed papers (Table 1) shows that AI has radically changed microprocessor development. The emergence of domain-specific designs, such as Google's TPUs and NVIDIA's tensor cores, emphasizes a more general industry trend toward hardware-software co-design (Figure 7, $R^2 = 0.92$), in which AI optimization becomes a strategic need rather than an option.

The competitive scene has also changed; NVIDIA, Intel, and Google are following different paths of invention (Table 3). Although NVIDIA leads in AI acceleration (27.21% of studies), Intel's hybrid architectures (32.16%) imply a balancing act between general-purpose computing and AI specialties. SME adoption, on the other hand, lags 3.2 times because of excessive 5 nm node development expenses ($540 M+), hence stressing an important market access disparity.

Strategic recommendations

The research suggests the following steps for businesses and legislators to take to make the most of these trends:

For chip makers:

- To satisfy sustainability goals, give energy-efficient designs a priority (e.g., Google's TPUs outperform GPUs by 2.8× in TOPS/watt).
- Invest in flexible designs, letting SMEs gradually integrate AI features without complete redesigns.

For governments and regulators:

- Support public-private R&D consortia to reduce obstacles to advanced node development (e.g., EU Chips Act model).
- Reduce market fragmentation using standardized benchmarking criteria for the performance of AI processors.

For industries of end-users (e.g., telecom, healthcare):

- Reduce latency by hastening edge AI deployments—e.g., 5G base stations with on-device inference.
- Work with chipmakers on domain-specific optimizations—for instance, medical imaging algorithms for healthcare GPUs.

Future research lines

Although this research offers a thorough overview of AI microprocessor developments, certain important issues still exist:

Longitudinal performance research:

- Monitor 3 nm/2 nm node adoption to evaluate whether Moore's law can be maintained using AI-driven design tools.

Economic feasibility:

- Using actual R&D spending data from TSMC, Intel, and Samsung, model the ROI of AI design automation.

Ethical and legal shortcomings:

- Look into algorithmic bias in AI processors used in sensitive contexts such as medical diagnosis and financial fraud detection.

Cross-disciplinary creativity:

- Investigate photonic and neuromorphic AI processors as substitutes for conventional von Neumann systems.

The AI microprocessor revolution is changing not only technology but also economic structures, legal systems, and worldwide competitiveness. The results imply that future success will rely on cooperative ecosystems—where end-users, software developers, and chip designers co-optimize hardware for developing AI tasks. By closing the study gaps mentioned above, academics and businesses can make sure these developments benefit society and the economy at large instead of aggravating current inequalities in technology access.

Acknowledgment

The author would like to thank all those involved in the work who made it possible to achieve the objectives of the research study.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data are available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Gabriel Silva-Atencio: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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How to Cite: Silva-Atencio, G. (2025). Competitive Intelligence Review: Evolution and Trends of AI-Based Microprocessors. *Archives of Advanced Engineering Science*. https://doi.org/10.47852/bonviewAAES52025603